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Omar M. Ashour, *The Pennsylvania State University*
Gül E. Kremer, *Iowa State University*
Carol Smith

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An Improved Triage Algorithm for Emergency Departments based on Fuzzy AHP and Utility Theory

Omar M. Ashour[1], Gül E. Okudan[1,2], and Carol A. Smith[3]
[1]Department of Industrial and Manufacturing Engineering
[2]School of Engineering Design
[3]School of Nursing
The Pennsylvania State University
University Park, PA, 16802, USA

Abstract

In Emergency Department (ED) settings, improving productivity, reducing patient waiting time, and increasing patient safety are important aspects. Decision making (DM) strategies and techniques are crucial to ameliorate relevant performance measures for these aspects. One critical DM process in EDs is the triage. The information gathered in triage might be uncertain due to many reasons, e.g., patient subjectivity and no relevant information available at this stage (e.g., X-rays). Accordingly, in this paper, we present a triage algorithm that uses Fuzzy Analytic Hierarchy Process (FAHP) along with the Multi-attribute Utility Theory (MAUT) to sort the patients. The FAHP takes into account the changing relative importance of the vital signs based on the primary complaint; thus, the status score reflects the severity due to the complaint and the vital sign levels. Three other attributes along with the status score help define the level of criticality: patient's age, gender and pain level. MAUT is used to aggregate the variables to arrive at a prioritization. We present the application of the proposed methodology using a clinical data set with actual patient information. Our results show multi-faceted improvements achieved through the use of the proposed method in comparison to the triage algorithm currently in place.

Keywords
Fuzzy Analytic Hierarchy Process, Multi-attribute Utility Theory; Triage; Emergency Department; Healthcare

1. Introduction

Emergency Departments (EDs) are considered as vital components of the nation's health care safety net [1], which are responsible for 45%-65% of hospital admissions [2]. Thus, the ED performance is a very critical issue. Most EDs in major areas are often overcrowded, and hence, hospitals utilize a triage system to sort patients according to the severity of the illness/injuries [3].

Many hospitals in the United States utilize the five-level emergency severity index (ESI) to sort patients into five groups with clinically meaningful differences in projected resource need and therefore, associated operational needs. The ESI designates the most acutely ill patients as level 1 (highest level) or 2, and uses the number of resources a patient needs to determine levels 3 to 5 (lowest level) [4]. Level-1 and 2 patients can be taken directly to the treatment area for rapid evaluation and treatment, while level-3 to 5 are sent to the waiting area [5]. This system does not consider prioritization of patients who are sent to wait (i.e., ESI levels 3-5); it assumes a first come first served routine.

Even though the number of resources is the primary decision rule to determine levels 3 to 5, physiological and descriptive variables can be used to determine a priority order for patients [6]. The physiological variables include heart rate, systolic and diastolic pressure, respiration rate, body temperature, and oxygen level. Indeed, Claudio and Okudan [6] presented a utility theory based patient prioritization, which takes into account the patient vital signs. The descriptive variables include age, gender, primary patient complaint, and pain level as described by the patient. Ashour and Okudan [7] presented a utility theory based approach accounting for the ESI, gender, age, and the pain level.

In the ED setting, the triage nurse assigns the ESI level, and then decides which patient will be treated first. The skills or the contextual factors that are needed to make accurate ED triage decisions are not known to this date; as the triage decision making is a complex process [8]. Much of the decision making is mainly based on nurse's experience [9], knowledge, and intuition [3]. However, Göransson et al. [8] presented findings revealing that the triage nurse decision making during ED triage varied, some studies showed that there is a difference between the expert and the beginner level nurses, while others found that less experienced and more experienced triage nurses' decision making was largely the same.

In general, patient prioritization is a decision making problem. Decisions in EDs involve a lot of uncertainty with respect to what a patient's illness and/or injuries are [6]. In addition, a study done by Fields et al. [10] investigated the discrepancies in decisions made across nurses in three clinical settings: Susquehanna Health Williamsport Hospital (SHWH), Mount Nittany Medical Center (MNMC), and Hershey Medical Center (HMC). In this study, Spearman's rank correlation comparison method was used. The results show that there are differences in patient rankings among nurses at different hospitals, and even within the same hospital.

This paper presents a new algorithm based on FAHP and MAUT that incorporates the vital signs while considering the uncertainty to solve the problem of prioritizing patients in EDs.

2. Literature Review

In a preliminary work [7], we used the utility theory to prioritize patients at the EDs. A clinical data set, from Susquehanna Health's Williamsport Hospital, was used to build the overall utility function. Patients' age range varied between 18 and 92. Patients were ranked based on emergency severity index (ESI) and three descriptive variables: age, gender and pain level. The utility theory takes into account the uncertainty that comes from the subjectivity in the decision making process, for example, the pain level (i.e., two patients might have the same symptoms and have the same illness/injury but one of them gives 5 and the other 8 out of ten for the pain level).
The overall utility function is shown below:

$$U(x\ ,x\ ,x\ ,x\ ) = \frac{}{} * ([-0.9569 * 0.5435 * (-0.250x\ + 1.236) + 1] * \ -0.9569 * 0.6016 * -0.02524\ + 0.01\ * \exp \frac{}{}\ + 1\ * \ -0.9569 * 0.1031 * \ -x1\ + 1\ * \ -0.9569 * 0.8000 * -0.09569\ + \ 0.09569 * \exp \frac{}{}\ + 1\ - 1) \quad (1)$$

Patel et al. [9] studied the decision making process of nurses in the general ED and concluded that nurses' decisions are based on generated hypotheses according to both the information given by the patient and on single symptoms perceived as being characteristic of diagnosis. Further, based on our interviews at clinical settings, while we have ascertained that the relative importance of vital signs changes across different complaints, neither the complaints nor the relative importance shifts were considered in the previous work. It should be noticed that vital signs were considered implicitly in the ESI level.

In ED settings, it is generally difficult to ascertain the patient information because of the dynamic nature of the patient status. For example, the vital signs change over time, and assessment of certain variables, such as, pain level, are subjective [10]. The use of fuzzy set theory allows the decision makers to incorporate unquantifiable information, incomplete information, non-obtainable information and partially ignorant facts into a decision model [11], and hence it is appropriate for such settings. The data relevant to the criteria (incomplete data) can be expressed as fuzzy data. The fuzzy data can be linguistic terms, fuzzy sets, or fuzzy numbers. If the fuzzy data are in linguistic terms, they are transformed into fuzzy numbers. Then, these numbers (or fuzzy sets) are assigned crisp scores.

Fuzzy logic is introduced to AHP to overcome its shortcomings [12]. Therefore, when the input information or the relations between criteria are imprecise or uncertain, the adoption of fuzzy logic is recommended. FAHP algorithm is described below [12]: 1) Construct a hierarchical structure for the problem to be solved; 2) Establish the fuzzy judgment matrix A and weight vector W; 3) Calculate weight numbers, from fuzzy scores of alternatives; then, 4) Rank the fuzzy scores to determine the optimum alternative.

The following section describes the proposed algorithm and presents the results of applying this algorithm on a real data set of 19 patients.

3. Proposed Algorithm and Results

Our proposed decision algorithm is illustrated in Figure 1. The process starts by identifying the patient status as one would in the current ESI algorithm [5]. Then, if the patient requires any immediate intervention, he is considered to be in "Critical State". After this stage, the procedure progresses as follows: 1) Is the patient in need of immediate intervention? If the response is affirmative, he is a "Critical State" patient. If not, he goes to Step 2; 2) The triage nurse asks the patient about his complaint, pain level, age, and gender, and takes his/her vital signs; 3) The complaint and the vital signs data are treated using the FAHP as explained above to yield what we referred to as "pretreated" data; 4) The data from Steps 2 and 3 is processed by the overall utility function to give the utility value for each patient; 5) Patients with high utility values go to the treatment area first, and the others with the lower value can wait in the waiting room. Then they are treated in descending order of priority based on the overall utility values. This algorithm is applied to a clinical data set as explained below.

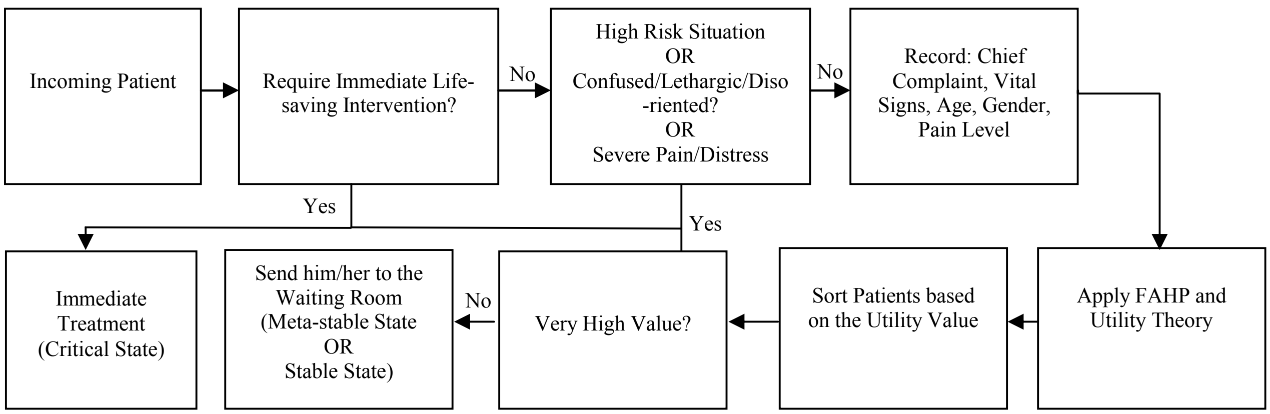

Figure 1: Proposed Algorithm

Table 1 shows the collected data set for 19 patients, where each patient record has the following information: the assigned ESI level, age, gender, pain level, systolic and diastolic blood pressure, pulse, respiration rate, body temperature, and oxygenation level (SaO2). These data were collected from the ED of Susquehanna Health's Williamsport Hospital. Susquehanna Health is a three-hospital health system including Divine Providence Hospital, Muncy Valley Hospital and the Williamsport Hospital & Medical Center located in north central Pennsylvania.

Every patient who comes to the ED has a chief complaint. These complaints are classified into17 categories as follows [13]: 1) Neurological Complaints; 2) Chest Pain Complaints; 3) Abdomen/Male; 4) Abdomen/Female; 5) Seizure; 6) Headache; 7) Psychiatric Complaints/Suicide Attempt; 8) Head/Face Trauma; 9) General Medicine Complaints; 10) Respiratory Complaints; 11) Alleged Assault; 12) Multiple Trauma; 13) Motor Vehicle Crash; 14) Extremity Complaint/Trauma; 15) Back Pain/Injury; 16) Skin Rash/Abscess; 17) Eye, Ear, Nose, Throat & Dental Complaints.

As shown in Step 2 (of Figure 1), the nurse records the patient complaint, and the physiological and descriptive variables. After that the nurse assigns the ESI level for the patient. Beyond what is commonly applied during triage as prescribed by Gilboy et al. [5], there is no systematic way to assign the ESI levels. Due to the presence of the uncertainty in taking such decisions we adopt the FAHP approach [12]. Our selection of this approach stems from the interviews we conducted with expert triage nurses. As per these interviews, we have identified that the relative importance of vital signs changes given the complaint the patient has. In other words, the triage nurse assigns weights to the vital signs unequally based on the patient complaint, and then identifies the ESI level based on that weighting. In order to ascertain how the relative importance weights of vital signs changes, we have conducted further interviews with expert triage nurses, where nurses rated each vital sign for their importance with respect to the patient complaint using the fuzzy number scale: Low (L), Relatively Low (RL), Medium (M), Relatively High (RH), and High (H), these linguistic terms associated with1, 3, 5, 7, and 9, respectively. The hierarchy of this problem would be the complaint type in the first level and the vital signs in the second level. In the FAHP, vital signs get different weights. In addition, each patient's vital signs are rated based on tables extracted with the aid of expert triage nurses. Then, the final score for each patient is calculated using the FAHP as illustrated by Lee et al. [12]. These scores are later converted via a utility function into utility values in order to calculate the overall utility value (or priority ranking) for each patient.

Table 1: Patients Data

	Complaint Description	ESI Number	Age	Gender	Pain Level	Systolic Blood Pressure	Diastolic Blood Pressure	Pulse	Respirat-ion Rate	Tempera-ture	SaO_2
1	Chest Pain Complaints	2	53	m	10	131	85	85	20	36.7	99
2	Abdomen/ Female	3	18	f	9	130	77	96	16	36.6	99
3	Extremity Complaint/ Trauma	3	48	m	4	98	68	96	18	37.8	97
4	General Medicine Complaints	3	76	f	3	143	81	104	20	36.8	94
5	Abdomen/ Male	3	20	m	7	117	79	69	20	36.3	100
6	Abdomen/ Male	3	75	m	8	132	53	90	16	36.5	97
7	Headache	3	49	f	9	157	92	83	16	36.3	97
8	Abdomen/ Female	2	54	f	20	159	99	70	32	37.1	98
9	Chest Pain Complaints	2	45	m	5	167	99	101	20	36.8	98
10	Headache	2	55	f	9	167	97	57	20	36.9	100
11	Abdomen/ Female	3	47	f	10	125	76	74	20	36.5	99
12	Psychiatric Complaints/ Suicide Attempt	3	22	m	0	136	77	86	16	36.4	100
13	General Medicine Complaints	3	58	f	0	117	73	65	22	35.6	96
14	Neurological Complaints	2	48	f	0	138	86	84	20	37	97
15	Abdomen/ Female	2	48	f	10	122	77	64	20	36	98
16	Chest Pain Complaints	2	62	f	0	124	78	83	20	36.8	99
17	Abdomen/ Female	3	19	f	2	113	68	74	18	36.7	98
18	General Medicine Complaints	3	57	m	2	132	87	75	20	36.3	95
19	General Medicine Complaints	2	73	f	0	147	80	84	14	37	97

The fuzzy judgment matrix for all patients is provided in Figure 2a. A MATLAB code was used to do the FAHP computation. After carrying out the fuzzy multiplication and addition, the fuzzy scores, the mean, and the standard deviation for all patients, which are shown in Figure 2b, are obtained. The utility function is built for the mean value. Thus, the patient complaint, which is better represented due to the more appropriate consideration of vital signs, will be considered in the overall utility value.

#	Systolic Blood Pressure	Diastolic Blood Pressure	Pulse	Respirat-ion Rate	Tempera-ture	SaO_2	Weight Vectors					
P1	3	3	1	1	1	1	1	9	9	9	9	9
P2	3	1	3	1	1	1	5	5	5	5	5	5
P3	1	1	3	1	7	1	1	5	5	5	5	5
P4	5	3	9	1	1	3	5	5	5	5	5	5
P5	1	1	1	1	3	1	5	5	5	5	5	5
P6	3	5	3	1	3	1	5	5	5	5	5	5
P7	5	5	1	1	3	1	1	5	5	5	3	3
P8	5	5	1	9	5	1	5	5	5	5	5	3
P9	7	5	9	1	1	1	1	9	9	9	9	9
P10	7	5	3	1	1	1	1	5	5	5	3	3
P11	3	1	1	1	3	1	5	5	5	5	5	3
P12	3	1	1	1	3	1	1	5	5	5	5	5
P13	1	1	1	5	3	1	5	5	5	5	5	5
P14	3	3	1	1	1	1	1	9	9	9	9	9
P15	3	1	1	1	3	1	5	5	5	5	5	3
P16	3	1	1	1	1	1	1	9	9	9	9	9
P17	1	1	5	1	1	1	5	5	5	5	5	3
P18	3	3	1	1	3	1	5	5	5	5	5	5
P19	5	1	1	3	1	1	5	5	5	5	5	5

a)

#	Fuzzy Scores			Mean	Standard Deviation
P1	36	52	168	85.33	0.8649
P2	18	50	154	74.00	0.8427
P3	28	66	170	88.00	0.9006
P4	42	100	224	122.00	1.4407
P5	18	40	140	66.00	0.7047
P6	24	80	196	100.00	1.2827
P7	24	60	168	84.00	0.9360
P8	52	118	246	138.67	1.6216
P9	96	112	252	153.33	1.2276
P10	22	58	162	80.67	0.8809
P11	16	48	148	70.67	0.7902
P12	16	38	134	62.67	0.6562
P13	24	60	168	84.00	0.9360
P14	36	52	168	85.33	0.8649
P15	16	48	148	70.67	0.7902
P16	36	38	150	74.67	0.7096
P17	22	48	148	72.67	0.7376
P18	18	60	168	82.00	0.9980
P19	24	60	168	84.00	0.9360

b)

Figure 2: a) Fuzzy Ratings of Patients with Respect to each Criterion and the Weight Vectors, b) Mean and Standard Deviation

The exponential distribution is used to model the utility functions for the variables: age, pain level, gender, and the "pretreated" value of the vital signs. Equation 2 shows the single utility function (SUF) for the "pretreated" value of the vital signs which is built using the procedure in Keeney and Raiffa [14].

$$\mathrm{U}\ (\mathrm{x}\ ) = -0.114978817\ +\ 0.099086806\exp^{(\ /\ \ \cdot\ \ )\ )} \qquad (2)$$

The attributes are not mutually preferentially independent, i.e., vital signs' "pretreated" value is not independent from the others, and hence a multiplicative aggregation form is adopted. The overall utility function combines all the physiological and descriptive variables. Single attribute utility functions for patient age, gender, and pain level, were used as developed in the preliminary work [7]. See equation 1 for x_2: patient age, x_3: patient gender and x_4: patient pain level. The new overall utility function is shown below, x_1: is the "pretreated" value of the vital signs.

$$\mathrm{U}(\mathrm{x}\ ,\mathrm{x}\ ,\mathrm{x}\ ,\mathrm{x}\ ) = \frac{}{.} * (\quad -0.9804 * 0.754 * \quad -0.114978817\ +\ 0.099086806 * \exp\frac{}{.} \quad + 1 \quad *$$
$$-0.9804 * 0.587 * \quad -0.02524\ + 0.01\ * \exp\frac{}{.} \quad + 1 \quad * \quad -0.9804 * 0.182 * \ -x1 \quad + 1 \quad * \quad -0.9804 *$$
$$0.800 * \quad -0.09569\ +\ 0.09569 * \exp\frac{}{.} \quad + 1 \quad - 1) \qquad (3)$$

Table 2: Patient Ranking Based on Utility Theory Function

#	ESI (x1*)	Mean (x1)	Age (x2)	Gender (x3)	Pain Level (x4)	U(x1*)	U(x1)	U(x2)	U(x3)	U(x4)	U(Patie-nt)	Overall Rank	U(Patien-t*)	Overall Rank*
P1	2	85.33	53	1	10	0.736	0.061	0.128	0.00	0.228	0.279	12	0.552	5
P2	3	74.00	18	2	9	0.486	0.048	0.000	1.00	0.191	0.333	9	0.444	13
P3	3	88.00	48	1	4	0.486	0.065	0.093	0.00	0.060	0.144	17	0.340	18
P4	3	122.00	76	2	3	0.486	0.111	0.474	1.00	0.042	0.479	2	0.550	6
P5	3	66.00	20	1	7	0.486	0.040	0.003	0.00	0.129	0.132	18	0.342	17
P6	3	100.00	75	1	8	0.486	0.080	0.449	0.00	0.158	0.396	4	0.536	8
P7	3	84.00	49	2	9	0.486	0.060	0.099	1.00	0.191	0.378	8	0.478	11
P8	2	138.67	54	2	20	0.736	0.138	0.136	1.00	1.000	0.870	1	0.919	1
P9	2	153.33	45	1	5	0.736	0.164	0.076	0.00	0.080	0.217	15	0.466	12
P10	2	80.67	55	2	9	0.736	0.056	0.144	1.00	0.191	0.394	5	0.590	4
P11	3	70.67	47	2	10	0.486	0.045	0.087	1.00	0.228	0.388	7	0.493	10
P12	3	62.67	22	1	0	0.486	0.036	0.006	0.00	0.000	0.031	19	0.267	19
P13	3	84.00	58	2	0	0.486	0.060	0.172	1.00	0.000	0.299	11	0.411	14
P14	2	85.33	48	2	0	0.736	0.061	0.093	1.00	0.000	0.263	13	0.495	9
P15	2	70.67	48	2	10	0.736	0.045	0.093	1.00	0.228	0.390	6	0.591	3
P16	2	74.67	62	2	0	0.736	0.049	0.218	1.00	0.000	0.314	10	0.536	7
P17	3	72.67	19	2	2	0.486	0.047	0.001	1.00	0.026	0.228	14	0.356	15
P18	3	82.00	57	1	2	0.486	0.058	0.163	0.00	0.026	0.153	16	0.352	16
P19	2	84.00	73	2	0	0.736	0.060	0.402	1.00	0.000	0.405	3	0.598	2

* Results based on the previous study (Ashour and Okudan, 2010)

Table 2 shows the ranking of the patients based on the results of this study and our preliminary work study [7]. For both studies, the first and the last patient in the rank are the same, patient #8 and patient #12. Even though, the rankings are different, due to incorporating the patient's chief complaint in the algorithm. The motivation behind correcting the previous function is that chief complaint has an impact on the decision making process at EDs. Patel et al. [9] concluded that the decision making process of nurses in the general ED is based on a generated hypotheses based on both the information given by the patient and on single symptoms (chief complaint) perceived as being characteristic of diagnosis. In the preliminary work we showed that a patient with ESI2-level should be served after a patient with an ESI3-level, and we explained that due to the nurse's decision making [7]. We also pointed out studies that showed the possibility of undertriage or overtriage [15-17].

4. Conclusions

Sorting patients in EDs is a decision making problem. This problem involves a lot of uncertainty as it depends on the nurse's knowledge, experience, and intuition and on the subjectivity of patient's attributes, such as, pain level. FAHP and the MAUT were selected to incorporate uncertainty appropriately to the decision making process.

FAHP and MAUT help DM to improve his consistency, reliability, and repeatability; which means the same decision can be suggested for the same scenario. Our model incorporates the physiological and the descriptive variables in one model. It can be used to sort patients based on vital signs, age, gender, and pain level; thus, it reduces the stress and the strain on triage nurses and improve service quality for patients. Moreover, the proposed methodology is a step in validating the triage nurse decisions. It should be acknowledged that using more data will improve the accuracy of the presented model. Overall, the algorithm presented is an aid to help the nurse making complex triage decision, and hence reduce the cognitive stress, improve productivity and the quality of the healthcare delivery in the EDs.

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